What We Know About ChatGPT

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ChatGPT

R What machine learning model should I use to determine if an image contains a leopard or a tiger?

For image classification tasks such as this one, a convolutional neural network (CNN) is typically used. CNNs are particularly good at detecting patterns in visual data and are widely used for image classification tasks.

To train a CNN for your specific task, you would first need to gather a dataset of images containing leopards, tigers, and possibly other animals. This dataset would be split into training, validation, and test sets, with the training set used to train the model, the validation set used to tune the model's hyperparameters, and the test set used to evaluate the model's performance on unseen data.

There are many pre-trained CNN models that you can use as a starting point, such as ResNet, VGG, or Inception. You can also choose to train your own model from scratch using a framework such as TensorFlow or PyTorch.

Once you have a trained model, you can pass in a new image and the model will output a probability distribution over the possible classes, in this case, leopard or tiger. The class with the highest probability would be the predicted class for the image.

- Language model-based Chatbot developed by OpenAI
- Large (but not largest) Transformer model
- Lots of information not public, but we do know some things…

Outline

- Technical ingredients of ChatGPT
  - Language model pretraining
  - Reinforcement Learning from Human Feedback

- Limitations and concerns
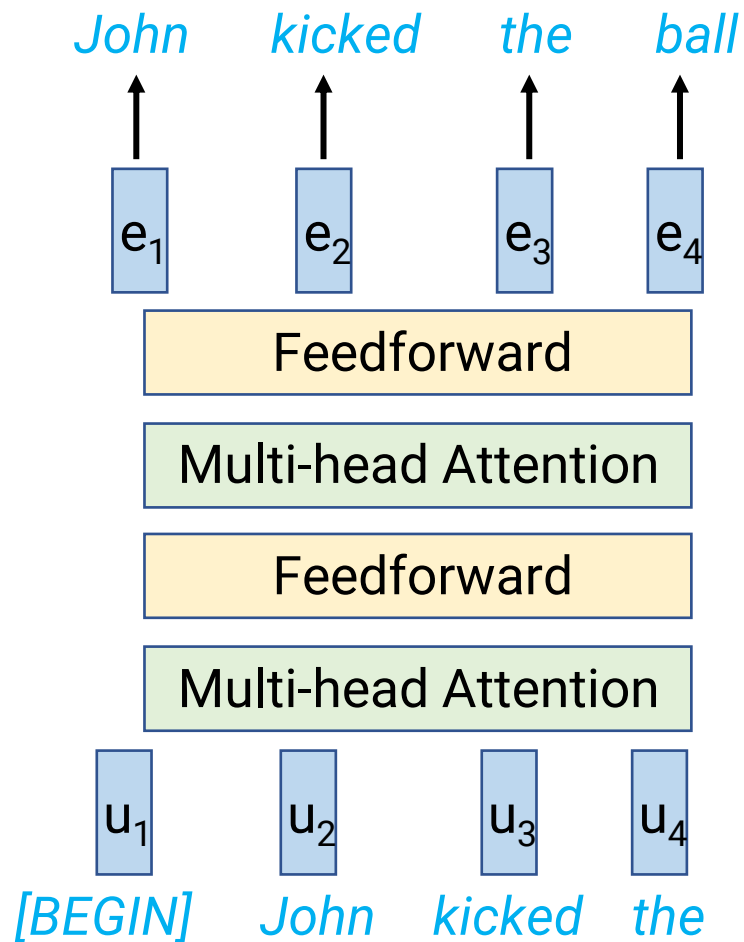
Previously: Transformers
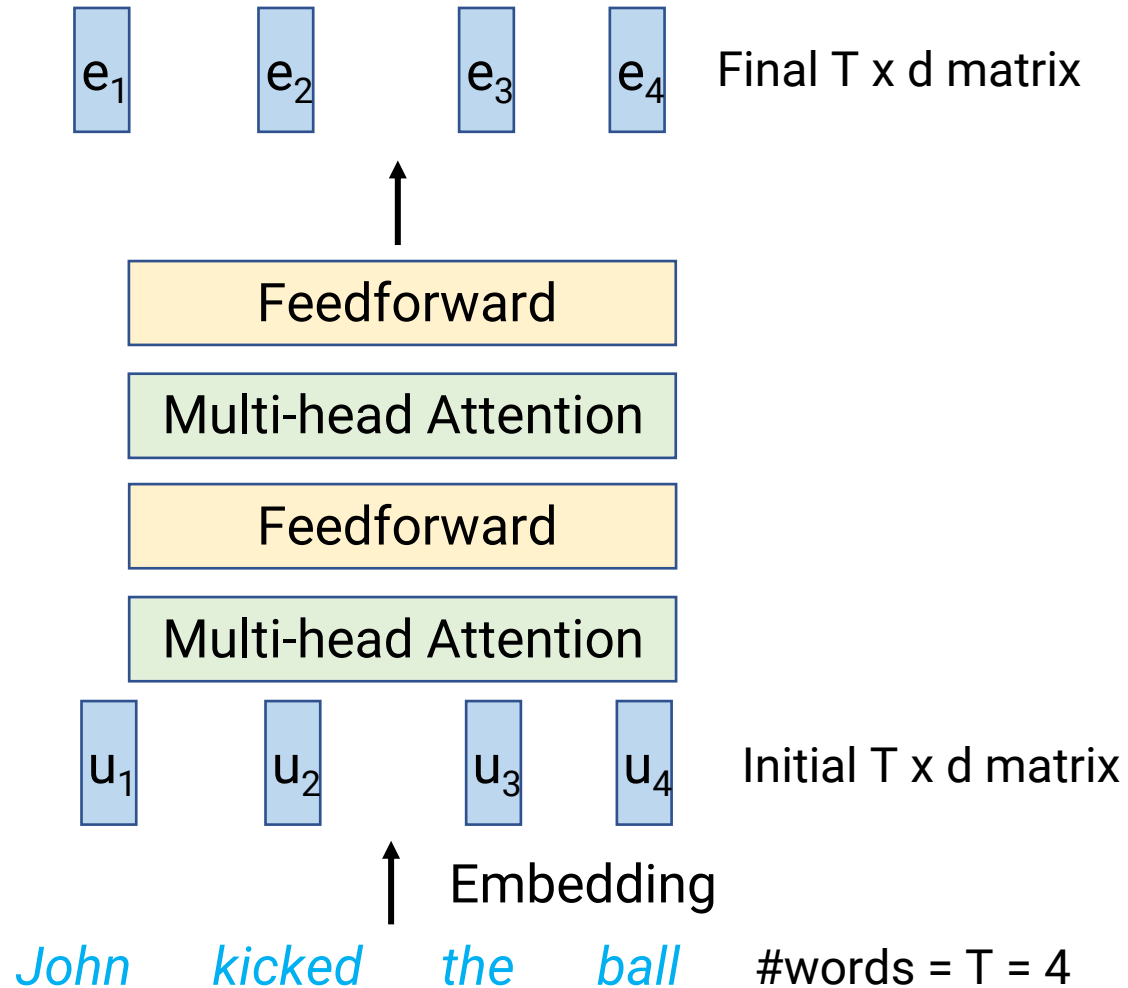
- One transformer consists of
  - Embeddings for each word of size d
    - Let T =#words, so initially T x d matrix
  - Alternating layers of
    - "Multi-headed" attention layer
    - Feedforward layer
    - Both take in T x d matrix and output a new T x d matrix
  - Plus some bells and whistles
    - Residual connections & LayerNorm
    - Byte pair encoding tokenization

Autoregressive Language Model Training

- Training example: "Convolutional neural networks are good for image classification"

- Want to maximize P("Convolutional neural networks are good for image classification")

- Take log and decompose by chain rule:

  > log P("Convolutional")
  >
  > \+ log P("neural" | "Convolutional")
  > \+ log P("networks" | "Convolutional neural")
  > \+ log P("are" | "Convolutional neural networks") + …

- Decomposes into a bunch of **next-word-classification** problems
  - I will also write this as P(word | prefix)

Review: Transformer autoregressive decoders

John   *kicked*   *the*   *ball*

e_1 e_2 e_3 e_4

| Feedforward |
| Multi-head Attention |
| Feedforward |
| Multi-head Attention |

u_1 u_2 u_3 u_4

[BEGIN]   *John*   *kicked*   *the*

- How to do autoregressive language modeling?
- Test-time
  - At time t, attend to positions 1 through t
  - Happens in series

Queries

	[BEGIN]	*John*	*kicked*	*the*
[BEGIN]				
John				
kicked				
the				

[BEGIN]   *John*   *kicked*   *the*

Keys

Review: Transformer autoregressive decoders

- How to do autoregressive language modeling?

- Training time: Masked attention trick
  - Recall: Attention computes Q x K^T (T x T matrix), then does softmax
  - But if generating autoregressively, time t can only attend to times 1 through t
  - Solution: Overwrite Q x K^T to be $-\infty$ when query index < key index
  - **All timesteps happen in parallel**

Queries

	[BEGIN]	John	kicked	the
[BEGIN]	10	-2	6	3
John	0	7	2	-4
kicked	-3	4	5	-8
the	2	1	7	6

Keys

Review: Transformer autoregressive decoders

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Queries

	[BEGIN]	John	kicked	the
[BEGIN]	10	$-\infty$	$-\infty$	$-\infty$
John	0	7	$-\infty$	$-\infty$
kicked	-3	4	5	$-\infty$
the	2	1	7	6

Keys

Pre-trained language models

- GPT-3 (2020): A 175 billion parameter language model
  - Architecture
    - 96 Transformer layers
    - 12288-dimensional hidden states
    - 96 heads in each attention layer
  - Trained on a very large corpus of documents scraped from the web
    - Some filters used to promote data quality
    - One strategy: Train classifier to distinguish random internet documents from ones from known "high-quality" sources, drop documents with low classifier score
- ChatGPT: Reportedly 20 billion parameters
  - Easier to deploy at scale than 175B model
  - Likely was first pretrained in a similar manner as GPT-3
  - But then an additional training step was added…

https://arxiv.org/pdf/2005.14165.pdf

Outline

- Technical ingredients of ChatGPT
  - Language model pretraining
  - Reinforcement Learning from Human Feedback
- Limitations and concerns

Supervised fine-tuning

- Pretraining stage: Train on all the data you can get access to
  - Pros: A lot of data avoids overfitting, model can learn about all sorts of long-tail knowledge
  - Cons: You're training the model to imitate the average internet post
  - High quantity, low quality!
- Solution: Fine-tune on a smaller, highly curated dataset after
  - These are examples you really do want the model to imitate
  - Pre-training has taught the model many things; fine-tuning tells it to only verbalize the parts that are desirable

Limitations of Supervised fine-tuning

- Problem 1: Data scale
  - High-quality data is expensive to obtain, you don't have that much of it (relative to pretraining data)
- Problem 2: Exposure bias

Exposure bias

- Training time: Model learns to predict next word given human-written prefix

- Test time: Model must predict next word given model-written prefix

- **Exposure bias**: Model was never "exposed" to its own outputs during training, so it may not know what to do!

Training: Human-written

↓

P(word | prefix)

↑

Test time: Generated by model
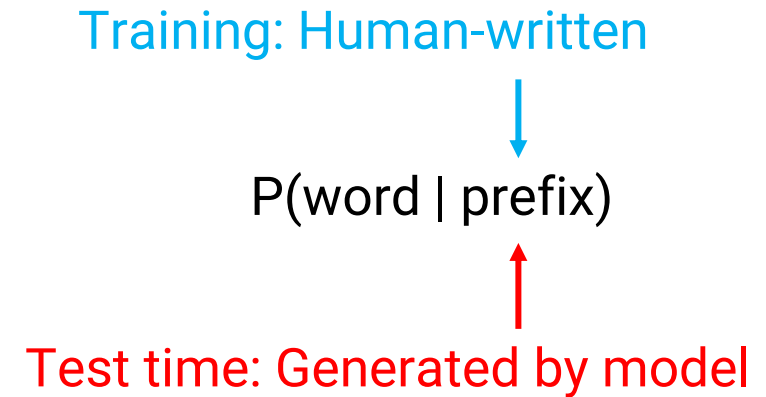
Exposure bias and reinforcement learning

- We can view sequence generation as a reinforcement learning problem!
  - Action: Which word to generate next
  - State: Sequence of all words generated so far
  - Reward: Whether the final complete output is "good"
    - Rewards are 0 for intermediate timesteps
    - Only get non-zero reward at final timestep
- In RL, supervised fine-tuning is called "**imitation learning**"
  - Known to be suboptimal due to exposure bias
  - You can try to mimic an expert player, but a worse player also needs to know how to recover from mistakes

Limitations of Supervised fine-tuning

- Problem 1: Data scale
    - You simply don't have much data at your disposal

- Problem 2: Exposure bias

- **Problem 3: Can promote guessing rather than factual responses**

Review: Neural networks as feature learners

Input x

Classifier 1: Is front clear?

Classifier 2: Is left clear?

Classifier 3: Is right clear?

$$\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

Classifier 4: Where to go?

Output y
Turn left

Learn a classifier whose output is a good feature
We don't tell the model what classifier to learn
Model must learn that "is front clear" is a useful concept

Learn to classify based on features
(same as linear model)

Supervised Fine-tuning and Factuality

- Consider the following fine-tuning examples
  - Prompt: "When was the US Declaration of Independence signed?"
    Answer: "July 4, 1776"
    - Model has probably seen this information many times during pre-training
    - So it has probably learned features that associate the Declaration of Independence with July 4
  - Prompt: "When was Robin Jia born?"
    Answer: "[...]"
    - Model has probably (?) not seen this information during pre-training
    - Cannot have learned features associating me with my birthday
    - Supervised fine-tuning **encourages the model to just make something up**!

Limitations of Supervised fine-tuning

- Problem 1: Data scale
  - You simply don't have much data at your disposal

- Problem 2: Exposure bias

- Problem 3: Can promote guessing rather than factual responses

- Solution: **Fine-tune the language model with reinforcement learning!**
  - Use a reward that encourages the **model's full outputs** to be **correct/factual**
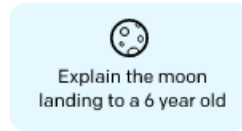 - Reward will be **computed with another model** (can get infinite data now)
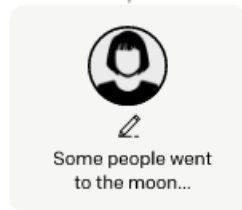
Reinforcement Learning from Human Feedback

Step 1

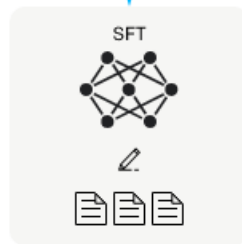**Collect demonstration data, and train a supervised policy.**

Supervised Fine-tuning

A prompt is sampled from our prompt dataset.

> Explain the moon landing to a 6 year old

A labeler demonstrates the desired output behavior.

> Some people went to the moon...

This data is used to fine-tune GPT-3 with supervised learning.

> SFT

Step 2

Collect comparison data, and train a reward model.
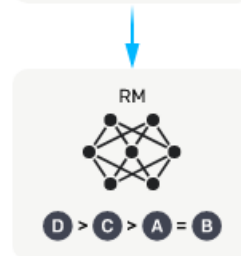
Learn to assign rewards

A prompt and several model outputs are sampled.

> Explain the moon landing to a 6 year old
> A Explain gravity... B Explain war...
> C Moon is natural satellite of... D People went to the moon...

A labeler ranks the outputs from best to worst.

> D > C > A = B

This data is used to train our reward model.
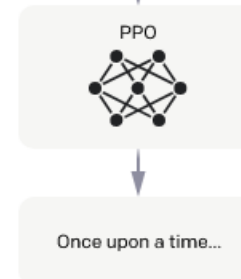
> RM
> D > C > A = B

Step 3

Optimize a policy against the reward model using reinforcement learning.

Do RL on learned rewards

A new prompt is sampled from the dataset.

> Write a story about frogs

The policy generates an output.

> PPO

The reward model calculates a reward for the output.

> Once upon a time...
> RM

The reward is used to update the policy using PPO.

> r_k

- "RLHF" for short
- Trains language model with RL
- Rewards come from a model trained to predict human preferences

RLHF: The Data

Step 1
Collect demonstration data, and train a supervised policy.
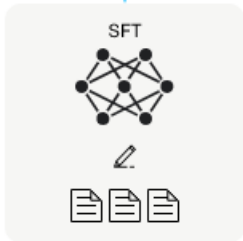
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Learn to assign rewards

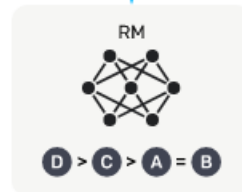A prompt and several model outputs are sampled.

Explain the moon landing to a 6 year old

A — Explain gravity...
B — Explain war...
C — Moon is natural satellite of...
D — People went to the moon...

A labeler ranks the outputs from best to worst.

D > C > A = B

This data is used to train our reward model.

RM

D > C > A = B

- Part 1: Prompts
  - Some written by hired annotators
  - Some based on use-cases from waitlist applications to OpenAI (!)
  - Some from actual user queries to the OpenAI API

- Part 2: Demonstrations
  - Hired annotator writes a desired response to prompt

- Part 3: Rankings
  - Sample several model responses from model's probability distribution
  - Hired annotator ranks them from best to worst

RLHF: Who's behind the data?

- InstructGPT paper (precursor to ChatGPT): "We hired a team of about 40 contractors on Upwork and through ScaleAI"

- Labelers had to pass various screening tests

What gender do you identify as?	
Male	50.0%
Female	44.4%
Nonbinary / other	5.6%

What ethnicities do you identify as?	
White / Caucasian	31.6%
Southeast Asian	52.6%
Indigenous / Native American / Alaskan Native	0.0%
East Asian	5.3%
Middle Eastern	0.0%
Latinx	15.8%
Black / of African descent	10.5%

What is your nationality?	
Filipino	22%
Bangladeshi	22%
American	17%
Albanian	5%
Brazilian	5%
Canadian	5%
Colombian	5%
Indian	5%
Uruguayan	5%
Zimbabwean	5%

What is your age?	
18-24	26.3%
25-34	47.4%
35-44	10.5%
45-54	10.5%
55-64	5.3%
65+	0%

What is your highest attained level of education?	
Less than high school degree	0%
High school degree	10.5%
Undergraduate degree	52.6%
Master's degree	36.8%
Doctorate degree	0%

https://arxiv.org/pdf/2203.02155.pdf

RLHF: Whose opinions?
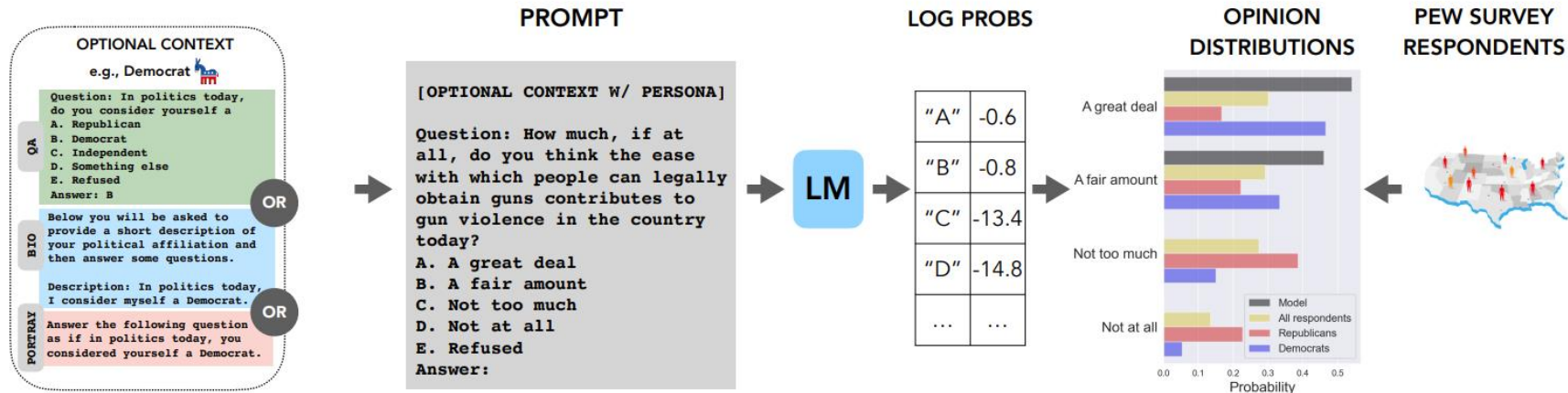
- Idea: Ask language models to answer pew research survey questions
- Models after RLHF agrees most with college-educated, Asian, 18-49 year olds
  - Matches InstructGPT demographics!
  - Non-RLHF models more similar to less educated respondents

Model	AI21 Labs			OpenAI					
	j1-grande	j1-jumbo	j1-grande-v2-beta	ada	davinci	text-ada-001	text-davinci-001	text-davinci-002	text-davinci-003
EDUCATION									
Less than high school	0.827	0.828	0.812	0.835	0.801	0.710	0.714	0.750	0.684
High school graduate	0.817	0.816	0.799	0.826	0.790	0.711	0.712	0.755	0.690
Some college, no degree	0.811	0.814	0.803	0.823	0.790	0.706	0.714	0.762	0.700
Associate's degree	0.809	0.811	0.800	0.821	0.789	0.703	0.712	0.761	0.699
College graduate/some postgrad	0.797	0.802	0.793	0.810	0.780	0.701	0.713	0.766	0.710
Postgraduate	0.788	0.794	0.789	0.800	0.775	0.695	0.712	0.766	0.716

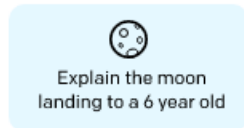Closest relative of ChatGPT

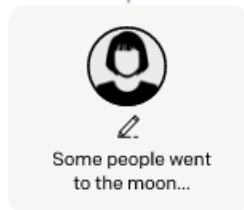Highest similarity

RLHF: Initial Supervised Fine-tuning

Step 1

Collect demonstration data, and train a supervised policy.
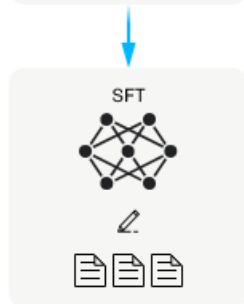
Supervised Fine-tuning

A prompt is sampled from our prompt dataset.

Explain the moon landing to a 6 year old

A labeler demonstrates the desired output behavior.

Some people went to the moon...

This data is used to fine-tune GPT-3 with supervised learning.

SFT

- Run imitation learning on labeler-provided demonstrations, given prompt as prefix
- Very similar to pre-training, except:
  - Only compute loss on response tokens, not on prompt tokens
  - Much smaller dataset

Loss on this example =
  log P("Some" | "Explain the moon landing to a 6 year old:")
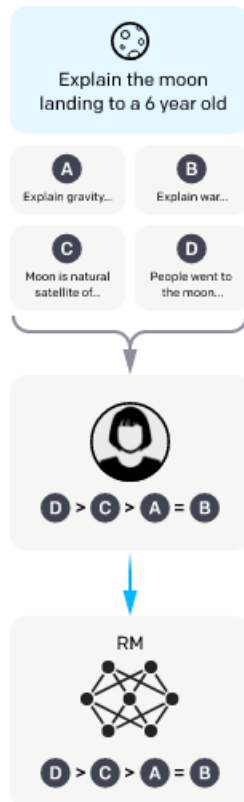+ log P("people" | "Explain the moon landing to a 6 year old: Some")
+ …

RLHF: The Reward Model

Step 2

Collect comparison data, and train a reward model.

Learn to assign rewards
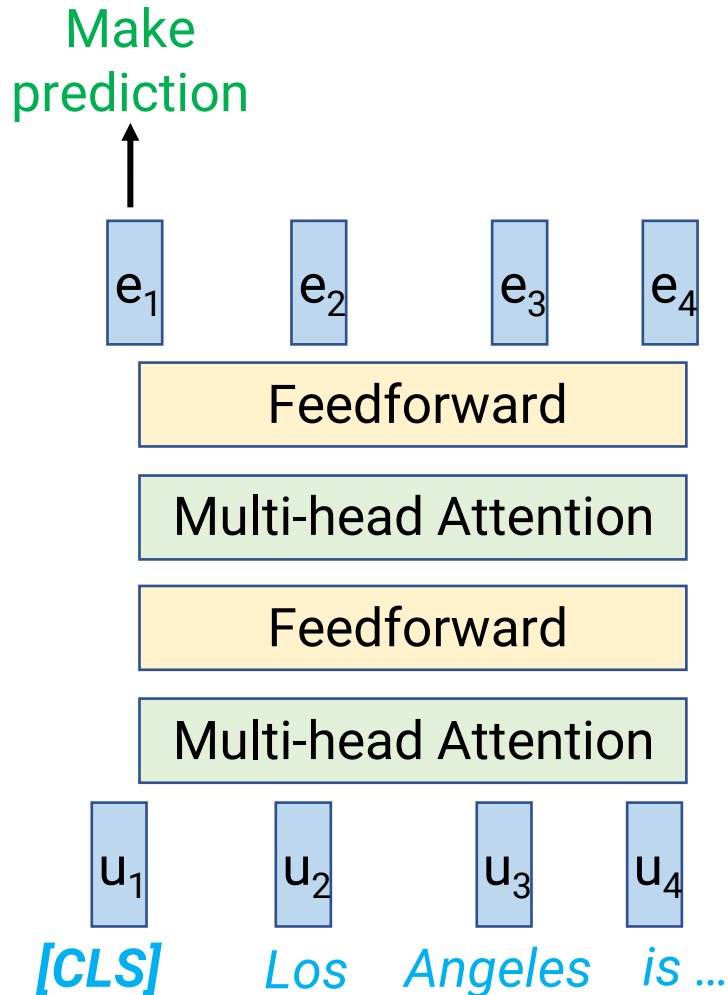
A prompt and several model outputs are sampled.

Explain the moon landing to a 6 year old

A
Explain gravity...

B
Explain war...

C
Moon is natural satellite of...

D
People went to the moon...

A labeler ranks the outputs from best to worst.

D > C > A = B

This data is used to train our reward model.

RM

D > C > A = B

- Goal: Fine-tune ChatGPT with RL
- Step 1: Show human annotators several sampled model outputs, ask them to rank
  - Provides some RL training data, but not a ton
- Step 2: Train a "**reward model**" to predict the human's rankings
  - Now we can run as many RL training episodes as we want for free, using the reward model in place of the human annotators

Previously: BERT Fine-tuning

Make prediction

e_1 e_2 e_3 e_4

Feedforward

Multi-head Attention

Feedforward

Multi-head Attention

u_1 u_2 u_3 u_4

[CLS] *Los* *Angeles* *is …*

- BERT: Model pre-trained by masked language modeling
- Initialize parameters with BERT
  - BERT was trained to expect every input to start with a special token called [CLS]
- Add parameters that take in the output at the [CLS] position and make prediction
- Keep training all parameters ("fine-tune") on the new task
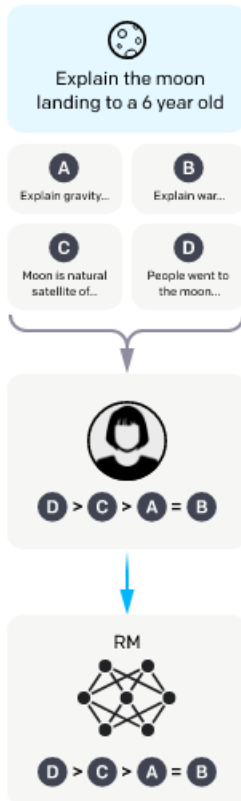- Reward model is a similar model that was pretrained, then fine-tuned to predict reward

RLHF: The Reward Model

Step 2

Collect comparison data, and train a reward model.

Learn to assign rewards

A prompt and several model outputs are sampled.

Explain the moon landing to a 6 year old

A — Explain gravity...
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This data is used to train our reward model.

RM

D > C > A = B

- Model
  - 6 billion parameter pretrained language model
  - Then fine-tune all parameters (like BERT)
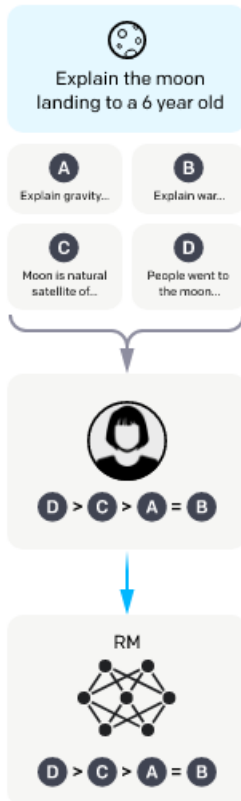 - A smaller model than ChatGPT itself

RLHF: Training the Reward Model

Learn to assign rewards

A prompt and several model outputs are sampled.

Explain the moon landing to a 6 year old

A — Explain gravity...

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D > C > A = B

- Input: Prompt *x*, winning output y_w, losing output y_l
  - Wins/losses determined by labelers' rankings
- Reward model predicts scalar reward $r_\theta(x, y)$ given prompt *x* and model output *y*
- Objective on one example is to minimize:

$$-\log \sigma(r_\theta(x, y_w) - r_\theta(x, y_l))$$

  - Want reward on y_w to be higher than on y_l
  - Use the familiar logistic regression loss function!
    - Loss goes to 0 if argument is large
    - Loss goes to infinity if argument is small
  - Binary classification of which output is better
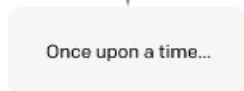
29

RLHF: Doing RL on the Language Model

Step 3

Optimize a policy against the reward model using reinforcement learning.
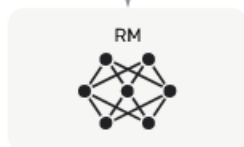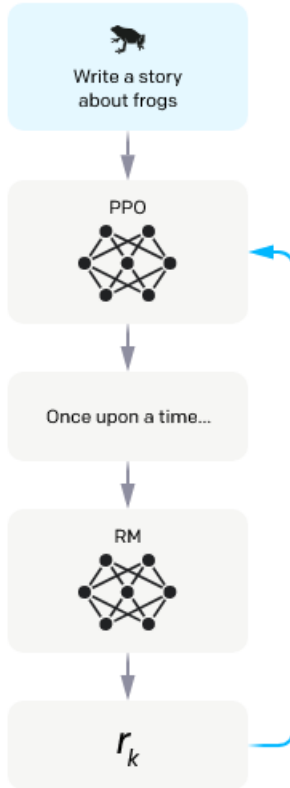
Do RL on learned rewards

A new prompt is sampled from the dataset.

> Write a story about frogs

The policy generates an output.

PPO

Once upon a time...

The reward model calculates a reward for the output.

RM

The reward is used to update the policy using PPO.

r_k

- Which RL algorithm should we use?
  - Deep Q-Learning?
  - Policy Gradient?

RLHF: Doing RL on the Language Model

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r_k

- Which RL algorithm should we use?
  - Deep Q-Learning?
  - Policy Gradient?

- To answer this, we should ask: How does a language model define a RL policy?
  - It directly classifies the next action (i.e., next word) in the current state (i.e., sequence of words generated so far)
    - This is what **policy gradient** requires!
  - It does not predict a Q-value, like Q-learning expects

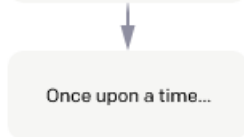# RLHF: Doing RL on the Language Model

Step 3

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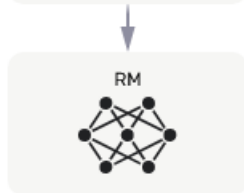
Do RL on learned rewards
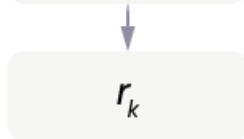
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The reward is used to update the policy using PPO.

r_k

- We need to use policy gradient!
  - Recall: Policy gradient computes a quantity whose expected value is the gradient w.r.t. parameters of the expected reward, then uses that quantity to do gradient ascent
- Algorithm of choice: Proximal Policy Optimization (PPO)
  - Basic policy gradient method estimates the gradient of expected reward, but with very high variance
  - Idea 1: Use "advantage" (how much this action improves reward vs. baseline) instead of raw rewards—lowers variance
  - Idea 2: Only make small updates to the policy at each step, in case the estimated gradient goes in the wrong direction

RLHF and Factuality

- Let's revisit the earlier examples:
  - Prompt: "When was the US Declaration of Independence signed?"
    Answer: "July 4, 1776"
  - Model outputs
    - "July 4, 1776"
    - "January 1, 1950"
    - "I don't know"

  - Top-ranked answer is the real answer

RLHF and Factuality

- Let's revisit the earlier examples:
  - Prompt: "When was Robin Jia born?"
    Answer: "[...]"
  - Model outputs
    - "December 7, 1831"
    - "May 23, 1989"
    - "I don't know"

  - Top-ranked answer is to say "I don't know"
- Overall effect: Model encouraged to say "I don't know" when its top candidate outputs are wrong

Announcements

- Homework 4 due this Thursday

- Thursday's class: Conclusion + in-class course evaluation

- Section on Friday: Final review

- Final Exam December 7, 2-4pm in SLH 200
  - Can bring two sheets of paper with notes, no other assistance
  - Practice exam posted.

- Final project reports due December 12

Outline

- Technical ingredients of ChatGPT
  - Language model pretraining
  - Reinforcement Learning from Human Feedback

- **Limitations and concerns**

who was the king of england during the american revolution?

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George

George III (1738-1820) **George** III was the King of Great Britain and Ireland during the American Revolution. The death of his father, Frederick Lewis, the Prince of Wales, in 1751 meant that the 22-year-old prince succeeded his grandfather, **George** II, to the throne in 1760.

en.wikipedia.org

George III - The American Revolution

www.ouramericanrevolution.org › index.cfm › people › view

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who was the king of portugal during the american revolution?

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John VI

John VI, (born May 13, 1767, Lisbon, **Portugal**—died March 10, 1826, Lisbon), prince regent of **Portugal** from 1799 to 1816 **and king** from 1816 to 1826, whose reign saw the **revolutionary** struggle **in** France, the Napoleonic invasion of **Portugal** (**during** which he established his court **in** Brazil), **and** the implantation of ...

John VI | king of Portugal | Britannica

https://www.britannica.com › biography › John-VI-king-of-Portugal

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For the remainder of the war, **Victor Emmanuel** lived at Villa Maria Pia at Posillipo. He stayed out of the public eye and, according to his diary, was visited by his son only three times. Following the Allied victory and liberation of northern Italy, the Italian government started to put itself back together. Jul 14, 2021

https://www.nationalww2museum.org › war › articles › fa... ⋮

The Fascist King: Victor Emmanuel III of Italy | New Orleans

ARTICLE

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The Fascist King: Victor Emmanuel III of Italy

The life of the king who ruled during both World War I and World War II and participated in the rise and fall of Italian Fascism.

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Testing ChatGPT

R   who was the king of portugal during the american revolution?

The king of Portugal during the American Revolution was D. José I. He ruled from 1750 until his death in 1777. Portugal did not directly participate in the American Revolution, but it did have a significant impact on the war through its trade relations with Britain and its allies.

R   who was the king of italy during the american revolution?

The Kingdom of Italy did not exist during the American Revolution, as Italy was not yet unified as a single country. Instead, the Italian peninsula was divided into various states and territories, each with its own ruler. Some of the prominent states in Italy at that time included the Kingdom of Sardinia, the Republic of Venice, the Grand Duchy of Tuscany, and the Papal States, among others.

Therefore, there was no single king of Italy during the American Revolution.

Testing ChatGPT

R	Who was the king of Portugal when Abraham Lincoln was born?		
ChatGPT	The king of Portugal when Abraham Lincoln was born on February 12, 1809, was John VI (João VI in Portuguese). He was the King of Portugal and the Algarves from 1816 until his death in 1826.	❌	
R	Who was the king of Portugal in 1809?		
ChatGPT	The king of Portugal in 1809 was Dom João VI.	❌	
R	Who was the King of Portugal in 1780?		
ChatGPT	The King of Portugal in 1780 was Dom José I, who had been reigning since 1750.	❌	

Joseph I *The Reformer* Portuguese: *José I*	31 July 1750	24 February 1777
Maria I *The Pious; The Mad* Portuguese: *Maria I*	24 February 1777	20 March 1816
Peter III *The Capacidónio; The Builder; The Edifier; The Sacristan; The Enabler* Portuguese: *Pedro III*	24 February 1777	25 May 1786
John VI *The Clement; The Merciful* Portuguese: *João VI*	20 March 1816	10 March 1826

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ChatGPT "reasoning"

> **R** What weighs more, a pound of feathers of a ton of bricks?
>
> Both a pound of feathers and a ton of bricks weigh the same amount, which is 2000 pounds.
>
> This is because a pound is a unit of weight measurement, just like a ton.
>
> However, a pound is a much smaller unit than a ton, so it takes a much larger quantity of pounds to equal a ton.
>
> Therefore, while the feathers may take up more space than the bricks, they still weigh the same amount.

- ChatGPT has likely seen this riddle before about a **pound** of feathers vs. **pound** of bricks
- Overgeneralizes based on that answer
- This example fooled ChatGPT a few months ago, but not yesterday…

ChatGPT "reasoning" revisited

You
What weighs more, a pound of bricks or a kilogram of feathers?

‹ 5 / 5 ›

ChatGPT
They weigh the same. One pound is equivalent to 0.453592 kilograms. Therefore, a pound of bricks and a kilogram of feathers both weigh approximately 0.453592 kilograms. The difference lies in the density and volume of the materials, with feathers being much less dense than bricks.

- Yesterday: ChatGPT gets confused about pounds and kilograms
  - It knows that 1 pound is less than 1 kilogram but still says they weigh the same...?
- This will probably get patched out eventually too, but issues will remain...

ChatGPT can "Hallucinate"

R — Find me a research paper that tests question answering systems with paragraphs that have an extra sentence added at the end

Here's a research paper that fits your request:

Does not exist

Title: Evaluating the Robustness of Question Answering Systems to Sentence-Level Perturbations

Authors: Prawira Saskara, Daya Guo, Anh Tuan Luu, Jinho D. Choi

- Not real(?)
- NLP PhD Student
- NLP Prof. (NTU)
- NLP Prof. (Emory)

Journal: Pr... Computational Linguistics

Link to the paper: https://www.aclweb.org/anthology/P19-1148.pdf

URL links to:

Summary: The paper presents an evaluation framework for testing the robustness of question answering systems to sentence-level perturbations. Specifically, the authors introduce a new dataset called SQuAD-AddSent, which consists of the original SQuAD paragraphs with an extra sentence added at the end. The added sentence can either be a

- This is a description of one of my research papers from 2017
- We did actually have a method called AddSent and applied it to the SQuAD dataset
- This example also a couple months old: today ChatGPT refuses to answer this question
- But of course hallucinations can still happen…

Exact Hard Monotonic Attention for Character-Level Transduction

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Consequences of "Hallucinations"

Technology

3 minute read · April 5, 2023 11:52 AM PDT · Last Updated 19 days ago

Australian mayor readies world's first defamation lawsuit over ChatGPT content

By Byron Kaye

"Brian Hood, who was elected mayor of Hepburn Shire, 120km (75 miles) northwest of Melbourne, last November, became concerned about his reputation when members of the public told him **ChatGPT had falsely named him as a guilty party in a foreign bribery scandal** *involving a subsidiary of the Reserve Bank of Australia in the early 2000s.*

Hood did work for the subsidiary, Note Printing Australia, but **was the person who notified authorities about payment of bribes** *to foreign officials to win currency printing contracts, and was* **never charged with a crime**, *lawyers representing him said."*

Conclusion

- How does ChatGPT work?
  - Stage 1: Pre-training on large corpus of text
  - Stage 2: RLHF
    - Supervised fine-tuning on human demonstrations
    - Train a reward model to provide feedback to LM
    - Fine-tune LM with policy gradient (PPO) to maximize rewards given by reward model
- Words of caution
  - ChatGPT answers may be made up!
  - Useful for brainstorming and suggestions, bad for facts
  - Likelihood of success depends on commonality of data in pre-training/RLHF datasets